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Cropland Productivity Evaluation: A 100 m Resolution Country Assessment Combining Earth Observation and Direct Measurements

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Abstract: A methodology is presented for the quantitative assessment of soil biomass productivity at 100 m spatial resolution on a national scale. The traditional land evaluation approach—where crop yield is the dependent variable—was followed using measured yield and net primary productivity data derived from satellite images, together with digital soil and climate maps. In addition to characterizing of soil biomass productivity based on measured data, the weight of soil properties on productivity was also quantified to provide measured soil health and soil quality indicators as an information base for designing sustainable land management practices. To produce these results, we used only the Random Forest method for our calculations. The study considers high-input agriculture, which is predominant in the country. Biomass productivity indices for the main crops (wheat, maize and sunflowers) and general productivity indices were calculated for the whole agricultural area of Hungary. Results can be implemented in cadastral systems, in applied in agricultural and rural development programs. The assessment can be repeated for monitoring purposes to support general monitoring objectives as well as for reporting in relation to the United Nations Sustainable Development Goals. However, on the basis of the results, we also propose a method for periodically updating the assessment, which can also be used for monitoring biomass productivity in the context of climate change, land degradation and the development of cultivation technology.

Keywords: random forest; land evaluation; soil; biomass; Hungary; gross primary productivity; soil health; soil quality

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Citation: Csikós, N.; Szabó, B.; Hermann, T.; Laborczi, A.; Matus, J.; Pásztor, L.; Szatmári, G.; Takács, K.; Tóth, G. Cropland Productivity Evaluation: A 100 m Resolution Country Assessment Combining Earth Observation and Direct Measurements. *Remote Sens.* **2023**, *15*, 1236. https://doi.org/10.3390/rs15051236

Academic Editors: Kenji Omasa, Shan Lu and Jie Wang

Received: 6 December 2022
Revised: 21 February 2023
Accepted: 22 February 2023
Published: 23 February 2023

1. Introduction

A key natural resource that ensures food security, ecological security and sustainable development is cultivable land. Recently, the importance of soil has been increasingly put into focus as the general public also become more aware of it as a non-renewable resource that can be lost quickly if improperly used or managed with very little chance of regeneration. Despite the critical importance of soil productivity, not only as indicator, but also in sustaining life on Earth, knowledge of the spatial and temporal variability of soil from regional to global scales is limited or fragmented. For the creation of effective agricultural and food policies at the regional levels, accurate soil productivity predictions are essential. The limited information on soil productivity hinders national (Farmers' Soil Conservation Programme, National Rural Development Programme) and international (EU Soil Mission) programs to monitoring its changes and build future scenarios on it.

The Sustainable Development Goals (SDGs) of the United Nations' Agenda 2030 framework include targets that recommend direct consideration of land and soil resources [1–3], which were adopted by all United Nations member states in 2015. Soil resources are linked to the SDGs through several soil functions [2], of which the biomass productivity function is at the core of SDGs 2.3 and 2.4., which explicitly target the sustainable increases in agricultural productivity. Furthermore, biomass productivity is proposed as an indicator of land degradation [4], which is linked to SGD 15.3 [5].

Biomass productivity is conditioned by inherent soil properties, climatic and management factors, thus variable in both space and time [6]. Spatial variability of soil productivity is traditionally assessed within the broad framework of land evaluation [7]. However, land evaluation should also include socio-economic components [8], which are not necessary for soil productivity evaluation. Nevertheless, soil is an integral part of the land with a distinct spatial location and therefore biophysical characteristics of the studied sites, such as climate and relief conditions, need to be taken into account when assessing its productivity [9].

The aim of classical quantitative land evaluation is to establish productivity indices based on actual yields in order to reflect production potentials for taxation and planning purposes [10–18]. A similar quantitative approach can be applied to reveal soil biomass productivity, its drivers and changes for monitoring purposes.

Dynamic and simulation models [7,16,19–22] can provide an alternative to classical productivity evaluation, but their validation still requires measured biomass or yield data. Advantages of the classical data-driven assessment, i.e., where yield is the dependent variable and biophysical factors are independent inputs, are high reliability, explicit spatial validity and easy interpretation. Process-based modeling and statistical modeling are also two frequently employed techniques for forecasting crop yield responses to climate variability. Process-based crop models are effective for predicting crop yields because they simulate physiological processes of crop growth and development in response to environmental factors and management techniques, especially at the field scale [23]. Traditional regression techniques have some drawbacks that can be addressed by statistical modeling techniques based on machine-learning algorithms. Machine-learning techniques have been used increasingly in recent years as niche-based classification modeling tools [24–26]. For our analysis we selected the Random Forest (RF) technique [27,28], which uses the Classification and Regression Trees method as the basis for growing multiple classification trees. The study considers high-input agriculture, which is predominant in the country and uses time series information (measured crop yield statistics and satellite-derived biomass productivity indicators).

A scientific-based biomass productivity assessment should be based on a numerical assessment of production potential based on statistical studies. Previous national land evaluation techniques were estimation procedures, which inevitably introduced classification errors. Since the only objective measure of land quality is yield over time, our method is designed with yield as the dependent variable and environmental factors (soil, climate, topography) that affect yield as the independent variables. The method must be designed in such a way that the parameterization process can be repeated as the amount of available data increases, so that the land classification system can be easily revised and refined at any time on the basis of changes in production conditions.

Based on the above considerations, we performed a detailed study with country coverage with the following aims: (i) to identify main soil and climatic determinants of biomass productivity, (ii) to quantify the weights of soil and climatic factors of productivity for the main crop types (wheat, maize, sunflowers), (iii) to produce crop-specific and general productivity maps for all agricultural land of the country, and (iv) to propose a methodology for integrated monitoring of biomass productivity.

2. Materials and Methods

Soil biomass productivity evaluation must be based on biomass data and the assessment of the environmental and management factors influencing it. This requires biomass data, and geographical and management data, including soil, topography, climate and fertilizer data. Country-wide implementation of the agricultural biomass productivity model can only be based on information that is available for the full agricultural area of the country. To ensure the best possible spatial detail to develop and implement a new productivity model, data of dependent variables (measured yield and remotely sensed biomass indicators) as well as independent variables on soil properties were collected at parcel scale and implemented at soil property maps of 100 m resolution.

2.1. Study Area

Hungary is located in Central Europe and the Carpathian Basin, which is a part of the Pannonian biogeographic region (45°43′ to 48°35′N and 16°06′ to 22°53′E). The country is 93,033 km^2 and has an elevation range between 77 and 1014 m above sea level, and agricultural lands are typically located between 77 and 350 m altitude. Agriculture is the dominant land use, with non-irrigated arable land (Figure 1) accounting for 61% of the country's total area [29]. Winter wheat (Triticum aestivum), maize (Zea mays) and sunflowers (Helianthus annuus), which have been sown on up to 80% of Hungary's arable land in recent decades, were selected for the productivity assessment.

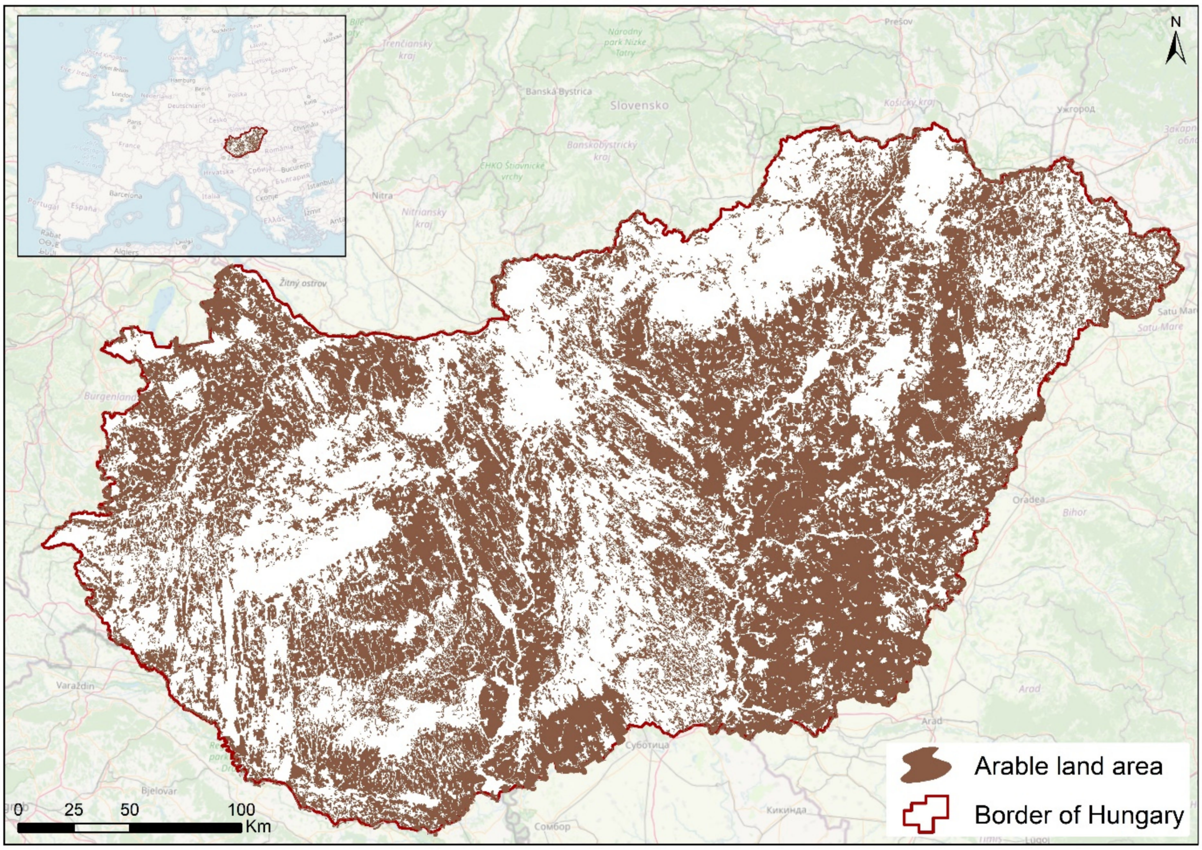

Figure 1. Arable land areas of Hungary (study area), based on Corine Land Cover 2018 dataset [30].

2.2. Databases

2.2.1. National Plot-Level Field Soil, Fertilization and Yield Databases (AIIR Field Database)

The AIIR database [31] contains crop type, yield, fertilization and soil information for each cultivated parcel, summing up to 80,000 cultivated parcels of Hungary for 5 years (1985–1989). The data were provided by the Central Plant and Soil Conservation Service (Budapest) for the purpose of land evaluation research. The sampling for the soil tests was carried out in such a way that the parcels were divided into 12 ha sections and then, along the diagonals of the selected sections, soil samples were taken from at least 20 locations using the so-called parallel sampling method. The subsamples were taken homogenized, so that an average sample was taken from the subplots of each agricultural field. For areas with a slope greater than 12%, average samples were taken separately for each (upper, middle, lower) section of the slope, taking into account erosion and different soil nutrient supply. The database was digitized in 2000 and in 2014 was upgraded to a modern geospatial database (point data with coordinates). We have selected the points that still fall on arable land at the time of our study. The database includes the following three major types of data:

- Basic data of the parcels (location, size, land user);
- Soil taxonomical and laboratory analysis data (soil type and subtype, pH, texture, organic matter, nitrogen, phosphorus and potassium content);
- Agricultural management data (crop type, yield, date of sowing, fertilization and harvest, fertilizer doses);
- Crop type and yield data.

Distribution of data by soil types is presented in Table 1.

Table 1. Main features of the AIIR dataset, based on Hungarian [32] and World Reference Base for Soil Resources [33] classification.

Soil Taxonomical Unit of Major Agricultural Soils		No. of Parcels Covered	Area (ha)	Area (%)
Hungarian classification	WRB 2014			
Lessivated brown forest soil (non-podzolic)	*Haplic Luvisol*	11,062	385,048	10.06
Raman-type brown forest soil	*Haplic Cambisol*	6567	270,239	7.06
Rust-brown sandy forest soil	*Arenic Cambisol*	2988	114,872	3
Typical calcareous chernozem	*Haplic Chernozems*	3792	228,240	5.96
Great Plains calcareous chernozem	*Haplic Chernozems*	2042	120,123	3.14
Carbonated meadow chernozem	*Gleyic Chernozems*	5540	330,200	8.63
Non-carbonated meadow chernozem	*Luvic Chernozems*	2021	108,149	2.83
Carbonated meadow soil	*Calcic Vertisols*	3952	184,853	4.83
Non-carbonated meadow soil	*Haplic Vertisols*	3460	151,394	3.96
Carbonated alluvial meadow soil	*Gleyic Fluvisols*	3129	142,535	3.73
Non-carbonated alluvial meadow soil	*Dystric Fluvisols*	4658	179,101	4.68
Carbonated humic alluvial soil	*Calcaric Fluvisols*	1210	51,720	1.35
Non-carbonated humic alluvial soil	*Dystric Fluvisols*	1584	50,789	1.33
Carbonated humic sandy soil	*Calcaric Cambisols*	3714	138,044	3.61
Non-carbonated humic sandy soil	*Dystric Cambisols*	2458	75,656	1.98
major soils in total		58,177	2,530,963	66.2
other soils		28,517	1,295,467	33.8
$\sum$		86,695	3,826,430	100

2.2.2. Remote Sensing Derived Biomass Productivity Indicators

Long term (2003–2018) time series remote sensing data were used to derive mean gross primary productivity (GPP) values as proposed by Jin and Eklundh (2014) [34]. The MODIS dataset (MOD17) [35] was used at a nominal 500 m spatial resolution to produce GPP datasets for the whole country. It is important to note that crop yields and GPP represent different aspects of productivity. However, in managed cropland there is a strong correlation between the two [36]. We used the normalized productivity (value range 1–100) as the target variable, and all of our results were normalized between 1 and 100, making it easier to integrate into our model.

2.2.3. Time Series Meteorological Data

The Central-European FORESEE meteorological database [37], which covers the whole area of the country with a 0.1 $\times$ 0.1 degree grid, was used to derive mean temperature and total precipitation at monthly scales (between 1951 and 2013). Mean temperature and precipitation values were linked to the spatial units (100 m pixels) of the assessment. The downscaling was performed by the bilinear resampling method.

2.2.4. Topographic Data

The Shuttle Radar Topography Mission [38,39] provides a dataset of 30 m resolution grid cells as the basis for the digital elevation model (DEM). SRTM mapped Earth's topography between 56 degrees south and 60 degrees north of the equator. SRTM has a vertical accuracy of 5.3 m (RMSE) in Hungary [40]. The SRTM-derived DEM was used to include a topographic component to the land evaluation model.

2.2.5. Land Use Data

The Hungarian coverage of the CORINE [30] land cover database for the year 2018 was used to delineate croplands in the country. The 1:100,000 scale datasets have a minimum mapping unit of 25 ha for patches and a minimum width of 100 m for linear elements. A total of 44 land cover and land use categories are included in the dataset, 28 of which are appropriate for Hungary [30]. All assessments and the map visualization of the results were based on the cropland areas (see Figure 1).

2.2.6. Map Series of Soil Types and Soil Properties

The unified national soil type and soil property maps of Pásztor et al. (2020, 2018, 2017, 2015) [41–44] provided the soil information base for the assessment. A total of 41 soil types, belonging to 9 main soil type groups of the Hungarian Soil Classification System [45], are covered by the dataset. Soil chemical and physical data include pH, calcium carbonate content, organic matter content and texture. The map series are all produced at a 100 m resolution and can be viewed on the dosoremi.hu website. The 100 m resolution of the soil maps was considered to be sufficiently detailed for parcel-scale productivity evaluation, and therefore this spatial resolution defined the resolution of the assessment. There is a slight difference in the semantic component of the soil type maps and the soil type information in the AIIR dataset (Table 1). There are soil types in the national soil map with areas covering <1% of the country that are not available in the AIIR dataset, or which are available only with a very limited sample size. These were not sufficient for statistical tests. This minor inconsistency required an expert-based modification of the final evaluation system.

2.3. Data Preparation

A quality and consistency check of the AIIR dataset was carried out in the first phase of the data preparation to filter out typos and false records. Inconsistent records (outliers), such as soil samples with high carbonate content and low pH, were excluded from the dataset. We then selected those records from the AIIR dataset that corresponded to agricultural parcels of intensive (i.e., high fertilizer use) cultivation. The selection was made based on the amount of fertilizers applied, and records containing at least 125 kg $\times$ ha^{-1} of nitrogen and 30 kg $\times$ ha^{-1} of active phosphorus input were kept. In this way, the analysis of the current assessment focused on data from intensively cultivated fields.

Winter wheat (*Triticum aestivum*), maize (*Zea mays*) and sunflowers (*Helianthus annuus*), which have been sown on up to 80% of the croplands in Hungary [46] in recent decades, were selected for the productivity evaluation. In order to establish a common basis for the analysis, the yield data of these three main crops from each parcel of the dataset were normalized to a scale of 1 to 100. For the same reason, the GPP values were also normalized to a scale of 1 to 100. Normalization was applied to all wheat, maize and sunflower yield data in the five years covered by the AIIR database and to all cropland pixels in the GPP dataset.

The AIIR database with normalized yield data and the normalized GPP dataset were integrated with the climate geodatabase into a single geodatabase using geographical coordinates as unique identifiers. The result was a georeferenced dataset created to include all soil, climate, management and yield data. Productivity analysis was carried out using information of the georeferenced pixels, including their geographical coordinates.

The GPP data, originally produced at 500 m resolution, were downscaled to 100 m resolution and normalized to values between 1 and 100. The downscaling was performed by the nearest neighbor resampling method The SRTM data, which were originally produced at 30 m resolution were generalized to 100 m resolution using the bilinear interpolation technique.

All datasets were converted to the Uniform National Projection System (EOV) to create a coherent geodatabase.

2.4. Assessment and Implementation Methods

2.4.1. Model Development

Soil biomass productivity assessment is the process of establishing relationships between soil properties and yields. Data-mining methods are tools for revealing hidden relationships in datasets structured by input variables. In soil assessment, data mining can help to identify the most important factors in yield formation and establish the weights of these factors. For our analysis we chose the Random Forest technique [27,28], which uses the Classification and Regression Trees method as a basis for growing multiple classification trees. For this operation, the database is divided into a series of training and test datasets to establish and validate relationships, respectively. Each training dataset (80% of the dataset) is a randomly selected subset that is used to develop a tree model using randomly selected predictors. The remaining data (10%) after the random selection of the subset (test data, 10% of dataset) are used to validate the developed model [47]. We used the createDataPartition function from the caret package to select data randomly. The generalized error of the forest depends on two parameters: how accurate each individual classifier is and how independent the different classifiers are from each other (i.e., the strength of each tree in the forest and the correlation between them). The Random Forest analysis was performed with the ranger R package [48]. The long-term means normalized productivity index (MNPI), taking into account both the measured AIIR data and the GPP data, was computed by taking the average of the two normalized datasets. The Random Forest operation was performed with the MNPI as the dependent variable and the environmental (soil, climate) variables as explanatory variables (Figure 2). First, the assessment was carried out separately for winter wheat, maize and sunflowers in order to evaluate crop-specific productivity of Hungarian croplands using the MNPI data of these crops. As a result, crop-specific productivity indices were produced for the three main crops. As our overall interest was to establish the MNPI for each Hungarian parcel at 100 m resolution, three parallel models were developed for the three major crops (wheat, maize, sunflowers) based on the crop-specific entries of the normalized yield data, and a fourth, a general productivity model, was developed based on the MNPI. As a result, both crop-specific (weighted means, wheat 40%, maize 40% and sunflowers 20%) and general productivity indices were assigned to climate and soil property combinations. Due to the limited information for some minor soil types (i.e., occupying area < 0.5% of agricultural lands), statistical testing could not be successfully performed for these soils. To assess the productivity evaluation of these soils, two evaluation approaches were applied and their results were combined. Firstly, an expert-based judgement was carried out. Productivity indices were established considering those of closely related soils in the Hungarian soil taxonomy using information from previous land evaluation systems [49], related literature [50–54] and expert knowledge. Secondly, a statistical test based solely on the GPP data was carried out to evaluate the effect of soil properties and climate, although without statistically significant results, but for orientation purposes. The relative importance of the explanatory variables was calculated. We analyzed the importance of all variables using the imp function of bclust package in R [55]. Relative importance was calculated by dividing the importance score of each variable by the largest importance score of the variable, and then multiplying by 100. Harmonizing the results of the two approaches ensured the consistency across the system, even for parcels with soils that make up a small proportion of the country's croplands. The theoretical range of the final productivity indices was set between 1 and 100, corresponding to the normalized yield values of the test dataset and following the indexing approach of traditional soil productivity evaluation of Hungary [51]. Model validation was performed using normalized yield data as independent variables of the test dataset. The test dataset included a randomly selected 10% of the data and a predict function of the ranger package was used. We calculated the correlation coefficient to show the relationship between the observed and the predicted values, the mean absolute error (MAE) to show the distance of the predicted values from the observed values [56], and the mean absolute percentage error (MAPE) to show the percentage of error between observed and predicted values [57].

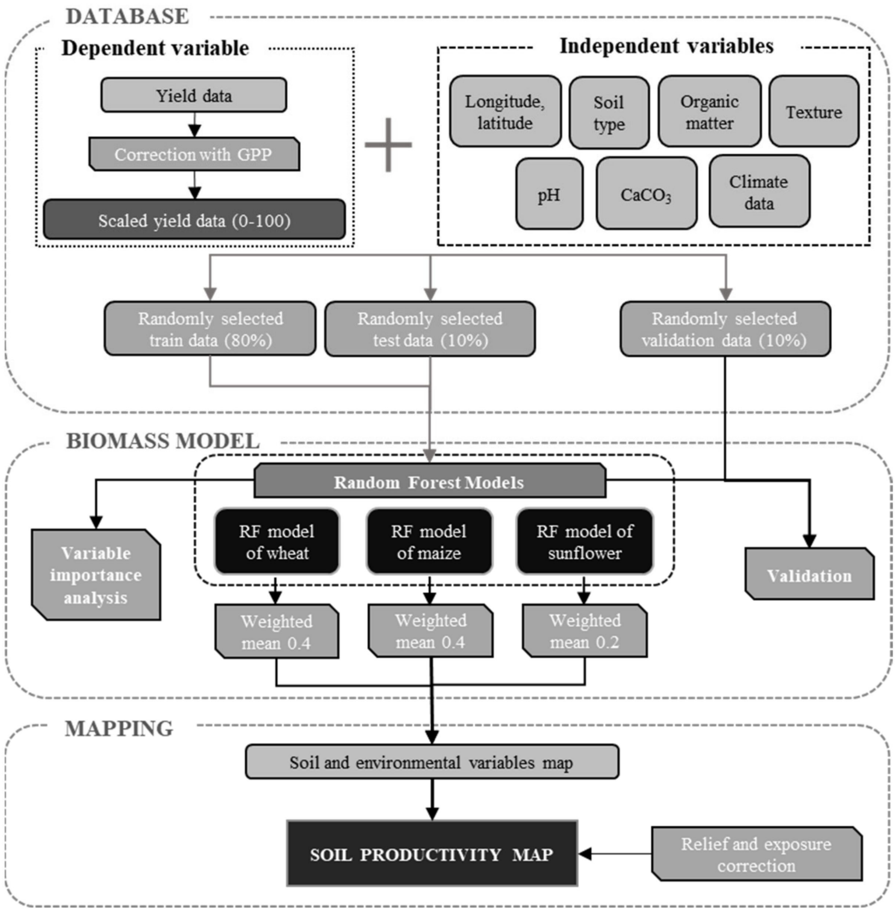

Figure 2. Flowchart of land evaluation modeling process.

2.4.2. Spatial Implementation

Soil, meteorological and digital terrain maps were used for the spatial implementation of the soil biomass productivity model, i.e., to produce soil productivity maps. The developed model provides productivity indices on a scale of 1 to 100 for several combinations of climate and soil properties in the country. Basic input layers for the spatial implementation include detailed (100 m) soil type and soil property maps and climate data. Slope correction coefficients (see Appendix A Table A1) from the previous official Hungarian land evaluation model [49] were applied to produce the final productivity indices. The coefficients reflect the effect of slope angle and slope direction on productivity. The SRTM digital topographic data were used to implement the correction coefficients and to produce the final maps. Presentation of the results covers all cropland areas of the country at a 100 m resolution.

3. Results

3.1. Model Development and Estimation Efficiency

The general, country-wide productivity model using biophysical explanatory variables explains up to 40% of the biomass productivity in the country (R^2 = 0.402). This model fit can be considered adequate for a country scale assessment, especially for a country with a wide variety of soil types from salt-affected soils to Arenosols, Luvisols and chernozems. The efficiency of the crop-specific models is best for wheat, followed by maize and sunflowers, in the order of the available sample size, respectively (Figure 3 and Table 2). Results were statistically significant at the 0.01 level.

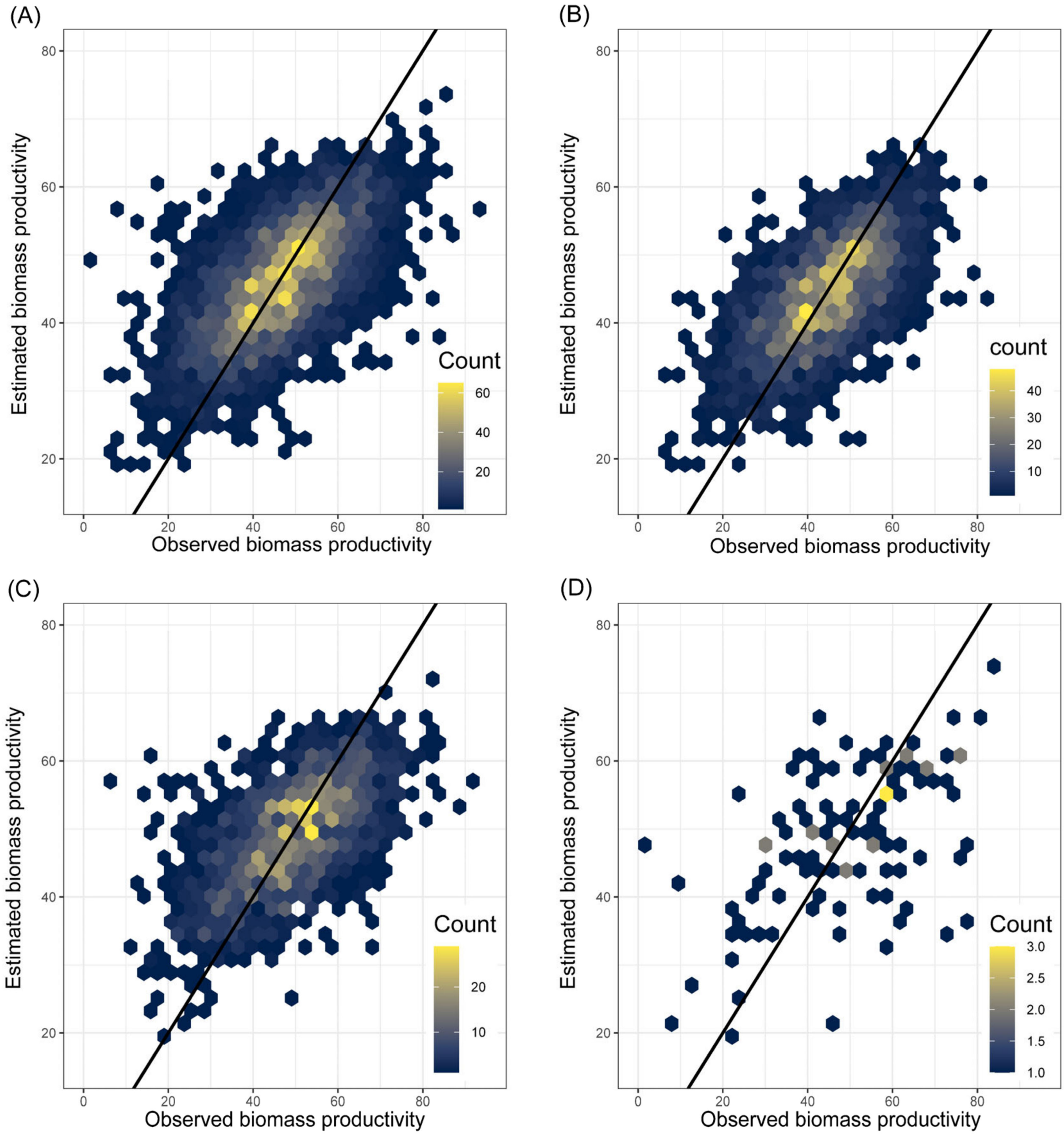

Figure 3. Scatter plot of observed vs estimated biomass productivity of total cropland area (**A**), wheat (**B**), maize (**C**) and sunflowers (**D**). Results were significant at the 0.01 level.

Table 2. Test validation results of all cropland, wheat, maize and sunflowers. R^2: correlation coefficient, R: Pearson correlation, MAPE: mean absolute percentage error, MAE: mean absolute error, N: number of pairs.

	R^2	R	MAPE (%)	MAE	N
All cropland	0.4	0.63	19.28	7.33	4381
Wheat	0.41	0.64	18.06	6.78	2631
Maize	0.35	0.59	19.17	7.93	1646
Sunflower	0.27	0.52	29.81	11.7	104

The combination of measured and satellite-driven data for the general productivity model development gave almost the same model fit as the crop-specific one for wheat, which was based on a large sample size of measured yields. The descriptive power of sunflower productivity estimation was not as strong (Figure 3D). The MAPE results are as follows: all cropland 19.28%, wheat 18.07%, maize 19.17% and sunflowers 29.81%. The most accurate prediction based on the MAPE and MAE results was for wheat followed by the maize and sunflower predictions.

3.2. Baseline Biomass Productivity Indices and Map for Croplands of Hungary

By implementing the biomass productivity model on the national soil, climate and topographic geodatabase, a new soil biomass productivity map was produced (Figure 4). The map shows the general productivity of croplands. In the same process, crop-specific productivity maps were also produced. While the crop-specific productivity indices and maps can be used for planning land use and cropping, the general productivity map provides an overview of the spatial pattern of biomass potential of agricultural parcels in the country.

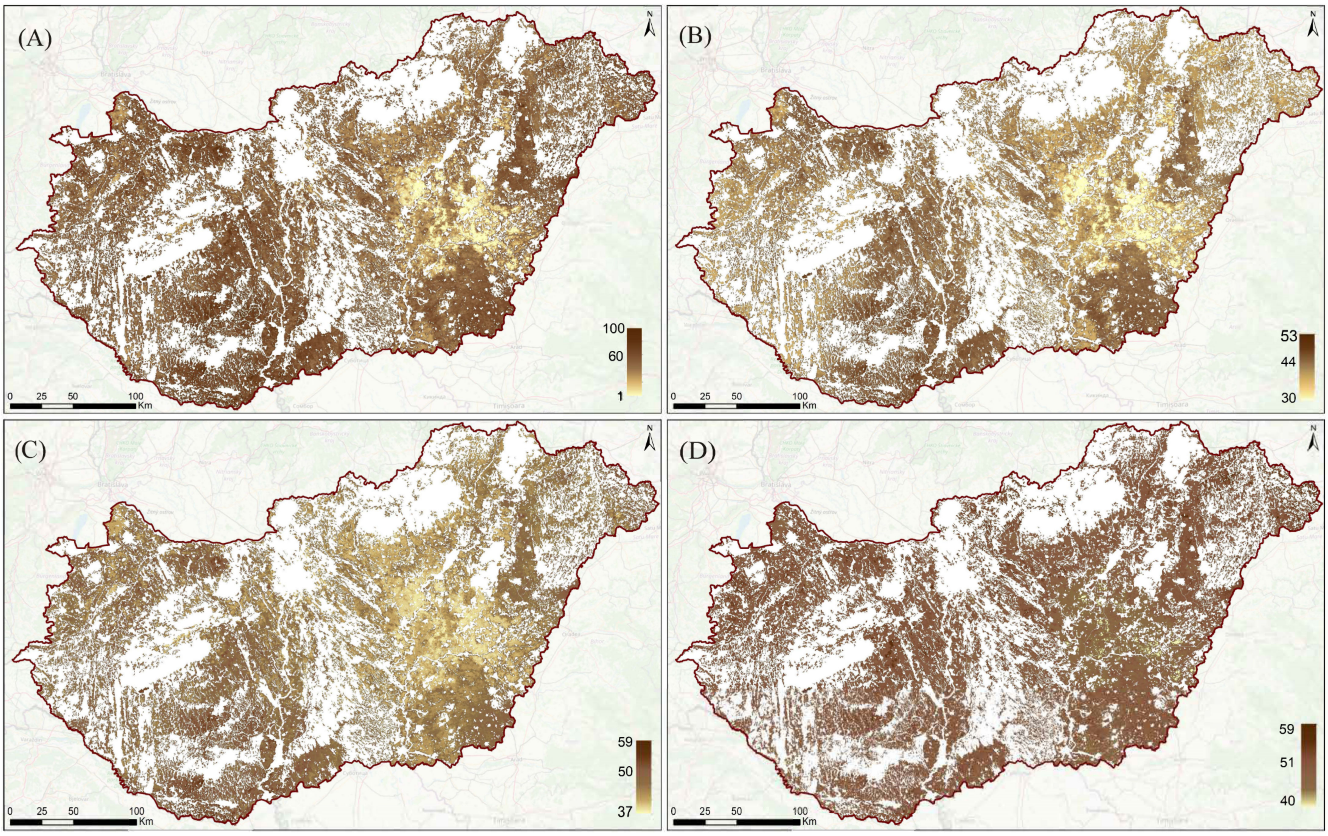

Figure 4. Croplands' land evaluation values range between 0 and 100 in the case of general biomass productivity of arable lands without slope correction coefficients (**A**) and separately wheat (**B**), maize (**C**) and sunflowers (**D**).

The map confirms the empirical knowledge that the most fertile areas are on chernozem soils in the east and on various loamy soils in the west of the country. Sandy soils, whether in the western, the central or the eastern part of the country, perform rather poorly. This phenomenon is typical of a country where water supply is the main climatic factor limiting crop production.

The mean productivity index for all the croplands is 64.7, with a standard deviation of 13.4, reflecting the dominancy of medium-to-good land within the agricultural areas of the country in terms of the spatial extent (Figure 4A).

The mean productivity index after slope coefficient correction for all the croplands of the country is 58.9, with a standard deviation of 18.5, reflecting the dominancy of medium-to-good land within the agricultural areas of the country (Figure 5).

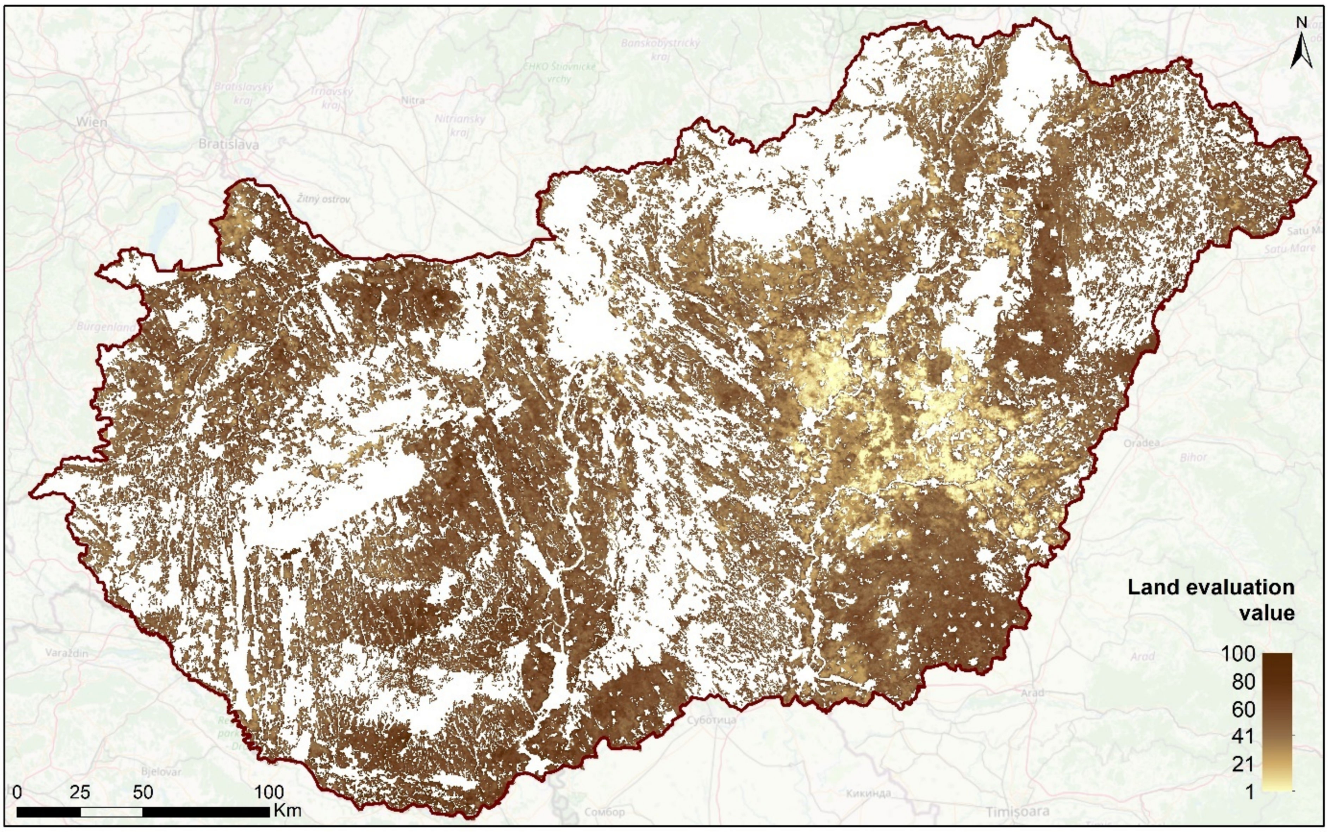

Figure 5. Croplands' land evaluation values range between 0 and 100 in the case of general biomass productivity of arable lands after slope correction.

3.3. Soil and Climatic Determinants of Biomass Productivity in Hungary

In general, humus content (which also reflects organic matter content), pH, $CaCO_3$ content, soil type and soil texture were the most important soil-based input parameters for predicting wheat productivity (Figure 6A). However, the geographical location was found to be an even more important explanatory variable. While this information suggests the importance of climate, the measured climatic variables ranked lower in the importance list. The mean temperatures of January, February, December and June (in the order of importance) are the most important thermal parameters for productivity. Regarding precipitation, the amounts in November, August, June and December are the most important determinants.

In the case of maize, on the other hand, the measured climatic variables were found to be of high importance, together with humus, pH, $CaCO_3$ and soil type, while the location was not considered to be relevant. These differences suggest the appropriateness of the crop-specific evaluation approach. There are also differences in the mean temperature and precipitation. Figure 6B shows that the precipitation (July, November, May, August and October) is a more important factor than temperature (most important in January and February) in the case of maize.

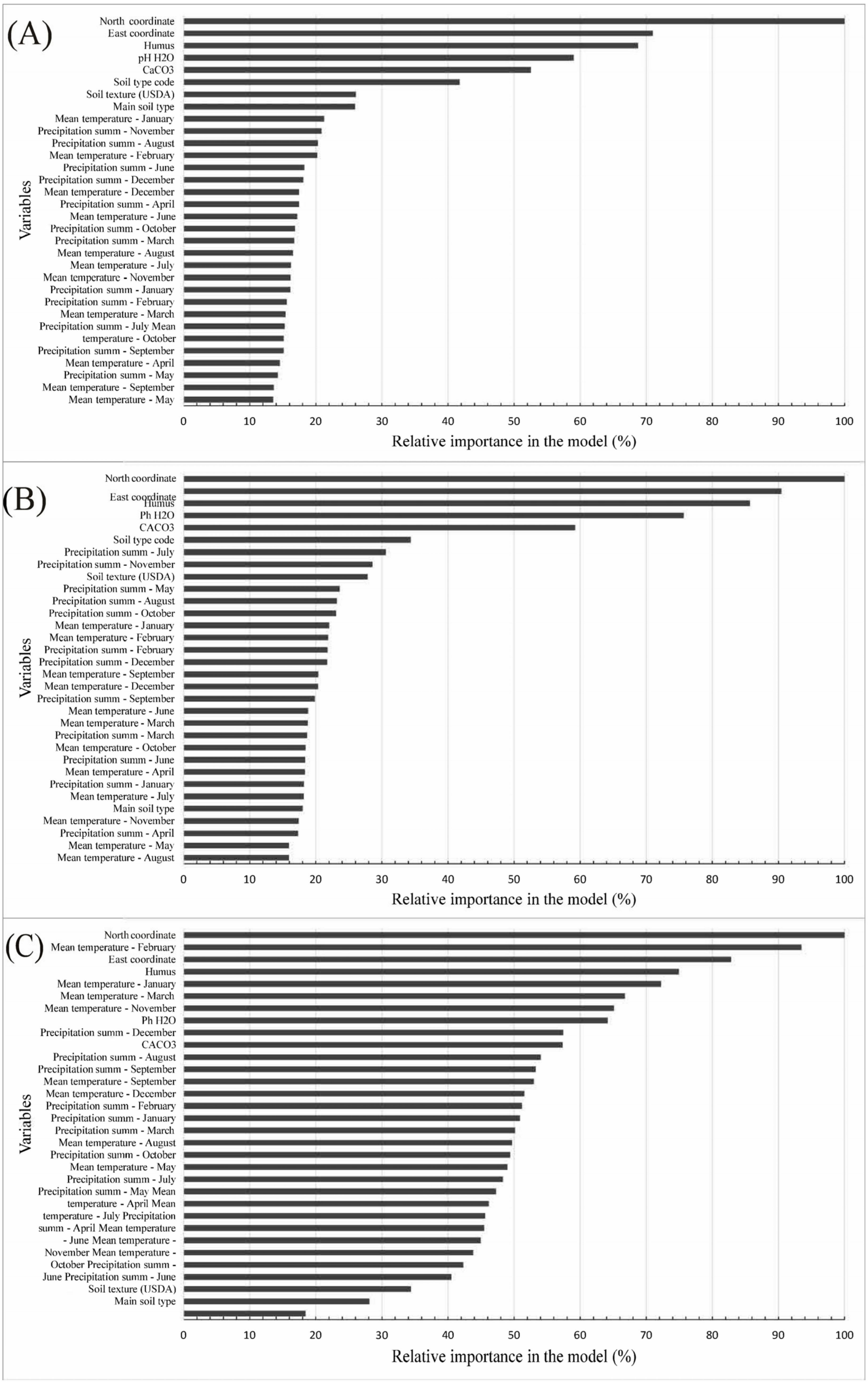

Figure 6. Overall importance of explanatory variables in predicting wheat (**A**), maize (**B**) and sunflower (**C**) biomass productivity.

Based on Figure 6C, the variables of the sunflower prediction show a completely different pattern. The most important variables are the location and mean temperature in February, followed by humus content, mean temperature in January, March and November, pH, precipitation in November and $CaCO_3$. Soil type and texture are the least important variables. Climatic variables (mainly amount of precipitation) have a more significant effect on the sunflower yield amount than the soil type and texture.

4. Discussion

Biomass productivity is a dynamic property that changes over time, partly due to changing climatic conditions (within and between years) and changing soil properties (pH, organic matter, soil nutrients content, etc.), but also due to new crop varieties and advances in crop management having an important influence. The effect of the changes in the biophysical factors may be synergistic or in the opposite direction. Nevertheless, it is possible to estimate the weight of the factors in productivity on a reasonable time scale. Twenty to thirty years seem to be an adequate time scale for estimating soil biomass productivity and for identifying the weights of different factors in it. A moving timeframe with intervals of 3 to 6 years can be proposed for the updating of the biomass productivity indices. If the system is to be used for monitoring purposes, soil biomass productivity will need to be compared on the basis of different time periods, e.g., on moving time windows or trends and supplemented by the monitoring of soil properties, subject to degradation. The moving time window for biomass productivity monitoring can be harmonized with the periodic assessments in soil monitoring, i.e., 3–6 years.

Our validation results (predicted data vs. measured data in the test set) showed that there is a significant difference in the prediction accuracy between the different crops. The sunflower model has a lower performance in calculating biomass productivity, which may be due to the fewer number of data available for model training. Furthermore, sunflowers are a cash crop grown on very diverse soils and not so much linked to bioclimatic factors and soil parameters [58,59], while the R^2 value (0.41) for the biomass productivity map can be regarded as adequate for a national estimate. The MAPE value indicates that only 18.06% of the model is inaccurate, that is, above the accuracy of results published in other studies [60,61]. The MAE indicator values indicate an average deviation of 6.78, which is not outstanding on a scale of 1 to 100. Cheng et al. (2022) [25] found similar R^2 values in the case of maize and wheat based on MODIS GPP values, with stronger correlation in the case of maize. However, other studies in the case of wheat presented lower values [24,61,62]. Although the performance of the sunflower productivity model is rather low, its inclusion in the assessment provides a more comprehensive overview of plant-specific productivities and their differences, including major factors and the varying weights of the factors in plant-specific productivities. Furthermore, the inclusion of an additional plant-specific model extends the potential of the applied method to provide a general soil productivity assessment considering multiple crops, which is often needed in land use planning.

A new soil biomass productivity map was created by applying the biomass productivity model using national soil, climate and topography geodatabase. Crop-specific productivity maps, which shall be the ultimate source of multicriteria land use planning [63], were also produced using the same technique. The spatial distribution of biomass potential is shown on the general productivity map, which can be used to plan land use and crop production. Further to that, weights of individual soil and climate parameters of crop-specific productivity indices were also derived. For our final model results (soil biomass productivity) we applied a correction that takes into account the topography. Slope angle and orientation both matter for solar radiation to be taken into account. Our solution for incorporating terrain indices from an earlier national land evaluation model [51] was tailored for Hungarian conditions (average slope under 2.3%), instead of applying more complex methods [64,65] used in other pedoclimatic conditions. Random Forest is considered to be an appropriate method to predict crop-specific biomass productivity, as proven by Jeon et al. [23] and as also highlighted in our country assessment. Results of

RF-based models can be applied to plan agricultural land use in order to increase the yield and make it sustainable, without environmental side effects. One of the most important and interesting results in our perspective is the quantification of the relative importance of explanatory variables, which best reflects the different edaphic and climatic needs of the observed crop species. For wheat, soil characteristics are the most important factors, while temperature and precipitation are less important [66]. In case of maize, soil parameters are still important but temperature and precipitation have more importance than in the case of wheat, highlighting that, even in a relatively small country like Hungary, climate tolerance of plants is a differentiating factor. This observation becomes more evident when studying sunflowers, where the importance of mean temperature and precipitation outweighs those of soil type and soil textures as earlier presented by Kern et al. (2018) in case studies from Hungary. Nevertheless climatic variables, such as precipitation in October and November and temperature in January and February are also important for winter wheat [66]. Our results also show the importance of summer rainfall totals (May, June, July) for maize, while for sunflowers the most important parameters are spring and autumn temperatures. We have to emphasize that it is often difficult to compare our results with those of other researchers, because the bioclimatic variables of the study area differ. For example, the work of Vannoppen and Gobin (2018) from northern Belgium, investigating the importance of climatic variables in winter wheat yield estimation, found similar parameters to be important, but in a different order. While in Hungary, the mean temperature in January and the amount of precipitation in November are the most important, in Belgium, winter precipitation is the most important [67]. The model fit can be further improved by adding information on management factors such as nutrient levels and fertilizer inputs [52,68].

Soil plays an important role in increasing crop production. The soil science community is trying to define the appropriate indicators. The presented analysis on the importance of variables in calculating productivity also provides a good basis for SDG indicators, as the related target of SDG is to improve land and soil quality progressively. Addressing soil health and soil quality are the main criteria for achieving sustainable agriculture. Climate change largely affects the minimum and maximum temperatures and the amount of precipitation per month [69–72]. Our results suggest that these variables are also important for winter wheat, maize and sunflowers, and that changes in these variables could change soil productivity in the future.

We established a baseline prediction model for biomass productivity applicable for Hungarian croplands using Earth observation data and yield statistics, identified the importance of soil and climatic determinants of biomass productivity, and proposed a methodology for integrated monitoring of biomass productivity.

5. Conclusions

Our present assessment shows the long-term productivity of soils in Hungary. Long-term productivity in this context means the mean productivity of the last three decades. A period of 20 to 30 years was found to be an adequate time scale for estimating the productivity of soil biomass and for identifying the weights of different factors in it, and also as prospective baseline and threshold values of soil health and soil quality indicators, which can be used in land degradation and soil improvement assessment. A new generalized biomass productivity map was created on a 100 m resolution, which can be implemented in the cadastral system and in multipurpose land use planning programs. The general map of productivity was produced from crop-specific productivity maps by applying biomass productivity models on the country-scale soil, climate and topography geodatabase. Soil properties and characteristics play the most important roles in wheat biomass productivity, while maize has a more significant relationship with precipitation. In the case of sunflowers, soil type and texture are less important factors. The spatial pattern of biomass potential is shown on the general productivity map at 100 m resolution. This map can be used to plan land use in general and agricultural production in croplands. Climate change largely affects the minimum and maximum temperatures, their variability and the amount of precipitation and its temporal distribution, which all have considerable impact on soil biomass productivity. The most important climatic variables for crops deserve particular attention in the next decade, particularly in developing adaptation strategies. We believe that our soil–climate-based land productivity models will help in developing new methods for such adaptation. However, in order to measure changes in biomass production potential, further assessment is required, including trend analysis and the analysis of the effects of changing combinations of soil properties. Nevertheless, the proposed methodology, in addition to possible applications in cadastral systems and in land use planning and agricultural development programs, is also applicable to the integrated monitoring of biomass productivity, which is in line with the goals related to the UN SDGs.

Author Contributions: Conceptualization, G.T., N.C. and B.S.; methodology, G.T., B.S., N.C. and G.S.; resources, L.P. and A.L.; writing—original draft preparation, B.S., G.T. and N.C.; writing—review and editing, N.C., B.S., T.H., A.L., J.M., L.P., G.S., K.T. and G.T.; visualization, N.C.; supervision, B.S. and G.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to private property.

Acknowledgments: We thank the anonymous referees for their valuable recommendations and suggestions.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Coefficients to modify the computed productivity based on slope relief and orientation [49].

Slope (%)	South, South-West	West, South-East	East, North-West	North-East	North
1	1	1	1	1	0.98
2	1	1	1	0.98	0.96
3	1	1	0.98	0.96	0.94
4	1	0.98	0.96	0.94	0.92
5	0.98	0.96	0.94	0.92	0.9
6	0.96	0.94	0.92	0.9	0.88
7	0.94	0.92	0.9	0.88	0.86
8	0.92	0.9	0.88	0.86	0.84
9	0.9	0.88	0.86	0.84	0.82
10	0.88	0.86	0.84	0.82	0.8
11	0.86	0.84	0.82	0.8	0.78
12	0.84	0.82	0.8	0.78	0.76
13	0.82	0.8	0.78	0.76	0.74
14	0.8	0.78	0.76	0.74	0.72
15	0.78	0.76	0.74	0.72	0.7
16	0.76	0.74	0.72	0.7	0.68
17	0.74	0.72	0.7	0.68	0.66
18	0.72	0.7	0.68	0.66	0.64
19	0.7	0.68	0.66	0.64	0.62
20	0.68	0.66	0.64	0.62	0.6
21	0.66	0.64	0.62	0.6	0.58
22	0.64	0.62	0.6	0.58	0.56
23	0.62	0.6	0.58	0.56	0.54
24	0.6	0.58	0.56	0.54	0.52
25	0.58	0.56	0.54	0.52	0.5
25	0.56	0.54	0.52	0.5	0.48

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